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From Boom to Bust in the Credit Cycle: the Role of Mortgage Credit

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Based on newly collected data on 37 economies over 1970-2012, we provide a rich description of 187 credit booms, credit busts and other episodes. We explore the changing composition of bank credit over the credit cycle. In an event analysis we chart changes in capital flows, regulation, productivity and house prices over credit booms and busts. We also ask which credit boom features are connected to a subsequent credit growth contraction. We find that the interaction of mortgage credit growth and increasing house prices is a good predictor of a credit boom. Credit booms in which the share of mortgage credit in total bank credit increases more, are credit booms which are more likely to 'go bad', leading to subsequent credit growth contractions.

JEL: E32; E44; E51

Keywords: Credit Cycle; Mortgages; Multinomial Logit Model

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I. Introduction

Credit crises are, in the celebrated phrase by Schularick and Taylor (2012), "credit booms gone bust"; but not all credit booms end in credit busts. The aim of this paper is to advance our understanding of the sequence and conditions of credit booms, credit busts and tranquil periods. We will refer to this sequence as the credit cycle. In particular, we contribute (1) a rich description of the changing composition of bank credit over the credit cycle, (2) an event analysis of the change in key variables including capital flows, regulation, productivity and house prices over credit booms and busts, and (3) an analysis of the role of household mortgage credit and house prices as warning signals for a credit crises.

Empirically, this required us to collect new data consistent with this differentiation, which cover 37 economies over 1970-2012. We distinguish in the analysis different types of bank credit in a cross-country consistent manner: bank loans to nonfinancial business, unsecured consumer credit to households, household mortgage credit, and bank credit to nonbank financial firms. Going beyond total credit-to-GDP aggregates, these distinctions follow from the different roles that these credit categories play in the credit-growth-crisis nexus.

This approach builds on, but also extends beyond, current research. A number of country studies have recently analyzed the macroeconomic effects of mortgage credit (Jimenez et al., 2012; Gan, 2007; Goodhart and Hofmann, 2008). The BIS completed a cross-economy data set on credit measures categories by borrowing sector in 2013 (Dembiermont et al., 2013). But to our knowledge, to date no cross-country study has charted credit composition over the credit cycle, and analyzed its effects on the probability of credit crisis.

We briefly preview the papers structure and key results. In the next section we locate the present study in the literature. In section III we present the new data and the identification of three credit cycle phases: credit 'boom', credit 'bust and 'normal' episodes, which are explored in section IV. About one third of all country–year observations is a credit boom and one third is a bust. The credit-GDP ratio grows faster in a boom than it drops in a bust. In emerging economies, credit busts are steeper and last longer, and normal periods are shorter than in advanced economies. But in advanced economies, two thirds of all booms are followed by bust, against less than half the booms in emerging countries. Normal periods are characterized by considerable increases in mortgage credit, particularly in advanced economies.

We find that a credit boom sees a simultaneous increase in both non-financial business credit and in mortgage credit. But during credit busts, non-financial business credit drops while household mortgage credit continues to increase as a share of GDP. The magnitude of 'bad' booms (followed by busts) is larger than of other booms (which we label 'good' booms). The share of mortgage credit in bad booms increases almost three times faster than is the case in good booms.

Section V presents results from an event analysis, exploring over the credit cycle the behavior of variables known to accompany credit booms: capital flows, financial regulation, house prices and productivity growth . This suggests a role for mortgage credit somewhat similar to capital flows. A rise is associated with a general credit boom, while a fall sets the scene for a credit crisis. Section VI presents the results from multinomial and binomial logit analysis of credit booms and busts. Two findings stand out. The interaction of house prices and mortgage credit is a good predictor of credit booms. And the probability of a credit boom 'going bust' is significantly increased if the share of mortgage credit in total credit rises. We also show that taking account of duration bias is important to these findings. Section VII concludes the paper with a summary of findings and policy implications.

II. Links to the Literature

The present study connects to the literatures on credit cycles, credit booms and early crisis warning signals. Credit cycles may be broadly defined as systematic variation in credit conditions (Bezemer, 2012), an observable measure for which is the expansion and contraction in credit supply over time. The empirical study of credit and financial cycles has been a focus of attention in the work of Borio (2013) and others at the BIS.[1] Building on credit cycle theories by Schumpeter (e.g. 1934) and Minsky (e.g., 1986), Borio (2013) describes the stylised empirical features of a long financial cycle (of around 16 years), as different from a shorter business cycle. Borio (2013) finds that the financial cycle can be characterized in terms of variations in credit supply and property prices, that its peaks coincide with financial crises, and that it helps detect financial distress risks well in advance. In another BIS paper, Drehmann et al. (2012) use turning and frequency-based filters to characterize the financial cycle. In common with other work (IMF, 2012), Drehmann et al. (2012) find that business cycle recessions are much deeper when they coincide with the contraction phase of the financial cycle. This motivates their closer study.

In this paper we follow a similar approach, based on turning points and a filter, to identify three credit cycle episodes. In the advanced-economies sample, these turn out to have a duration of 5, 4 and 7 years, so 16 years in total (14 years in the total sample). Thus, we are studying a cycle similar in duration to the financial cycle.[2] We also observe in section V joint fluctuations of credit and property prices, which Drehmann et al. (2012) identify for the financial cycle. A third common feature is that we link the credit cycle to financial stress in the form of a credit growth contraction.

A larger literature studies credit booms, which is one phase in the credit cycle. One strand analyzes the determinants of credit booms, which include capital inflows (especially, debt inflows), loose monetary policy, deregulation and financial reforms, domestic demand expansion and rising net imports (Mendoza and Terrones, 2012; Ostry et al., 2011; Borio et al., 2011; Bruno and Shin, 2013; Furceri

[1] For theoretical treatments of the credit cycle, see e.g. Kiyotaki and Moore (1997); Boissay et al. (2013).

[2] Since the cycle in the present paper is identified in a different way from the financial cycle in the work of Borio, Drehman and others, we will refer to it as the 'credit cycle' so as to avoid confusion.

et al., 2012; Magud et al., 2012; Calderon and Kubota, 2012; Elekdag and Wu, 2013; Lane and McQuade, 2014). We build on this literature when estimating boom and bust probabilites in section VI. Another strand analyzes the consequences of credit booms, which Elekdag and Wu (2013) aptly characterize as either 'boon' or 'boom-bust'. Financial crises are invariably associated with a credit 'bust' (i.e., a contraction in the growth rate of credit, possibly into negative territory), which is often preceded by a credit boom (mostly defined as above-trend credit growth). But the reverse is not true: not all credit booms end in busts (Ranciere et al., 2008; Mendoza and Terrones, 2012; Barajas et al., 2007).

We add to this literature by distinguishing between 'boon' and 'boom-bust' into what we label 'good' and 'bad' booms, by analyzing the determinants of that distinction during the credit cycle, and by study the evolution of credit composition over the cycle. Several findings point to the need to analyze credit aggregates characterized by borrowing categories. For instance, Kalemli-Ozcan et al. (2012) show that "excessive risk taking before the crisis was not easily detectable because the risk involved the quality rather than the amount of assets". Quality of loan assets is likely to be connected to type of borrower and collateral status, such that household mortgage credit will pose different risks of crisis than loans to nonfinancial business. This motivates the distinctions we will make in the present study.

In addition, a number of recent studies identified the problematic effects of household credit. Since in OECD economies, household credit is mostly mortgage credit, these findings translate into caution with regard to the growth of mortgage credit. Economies with more household credit tend to have larger external imbalances, greater risk of crisis and recession and - once struck by crisis - suffer they more output loss (Büyükkarabacak and Krause, 2009; Büyükkarabacak and Valev, 2010; IMF, 2011; Mian et al., 2013). In addition, and different from unsecured household consumption credit, mortgage credit interacts with house prices. Several studies show that the joint increase of private leverage and asset pries builds financial fragility and stress (Borio and Lowe, 2004; Mendoza and Terrones, 2012; Davis and Zhu, 2009). This motivates our regression analysis, where we interact house price increases with the growth of mortgage credit.

Our paper also connects to the literatures on financial fragility and on early warning signals for financial crises. In an early empirical study for 53 countries over 1980-95, Demirguc-Kent and Detragiache (1998) find that financial liberalization increase the risk of financial crisis. This finding is confirmed in a number of subsequent studies, including (Reinhart and Rogoff, 2009). Expansion of credit and leverage, often resulting from financial liberalization and financial innovation (Beck et al., 2012) are other crisis risk indicators (Gourinchas and Obstfeld, 2012; Mendoza and Terrones, 2012; Bussiere and Fratzscher, 2006). Capital account openness and capital flows are an other risk factor Kaminsky and Schmukler (2008), as is currency appreciation Gourinchas and Obstfeld (2012); Bussiere and Fratzscher (2006). Including the composition of bank credit, captured in the share of household mortgage loans in total credit may help improve the measurement of financial sector fragilities which lead to credit growth contractions and financial crisis.

III. Credit Booms and Busts: Data and Identification

A. Data

Our sample covers 37 advanced and emerging economies over the period 1970-2012. Our data includes bank credit decomposed into four different categories: nonfinancial business credit, consumption credit, mortgages and financial business credit. We refer to Bezemer et al. (2014) for a detailed description of this newly constructed dataset. In addition we use economy-level data from various sources, described in the next section. First we turn to the definition and measurement of credit booms and credit busts.

B. *Identification of credit booms and busts*

We identify three phases of the credit cycle: credit booms, credit busts and normal periods. Different approaches have been proposed in the literature for constructing chronologies of credit cycles and there is no consensus on the preferable methodology. However, a "good methodology should be simple to implement, reasonably objective (i.e. does not depend on the judgment of the analyst) and yield plausible results (Agnello and Schuknecht, 2011). In the present paper, we identify credit booms and busts as deviations from long-term trends in total credit stocks, similar to the work by Braun and Larrain (2005) on business cycles.

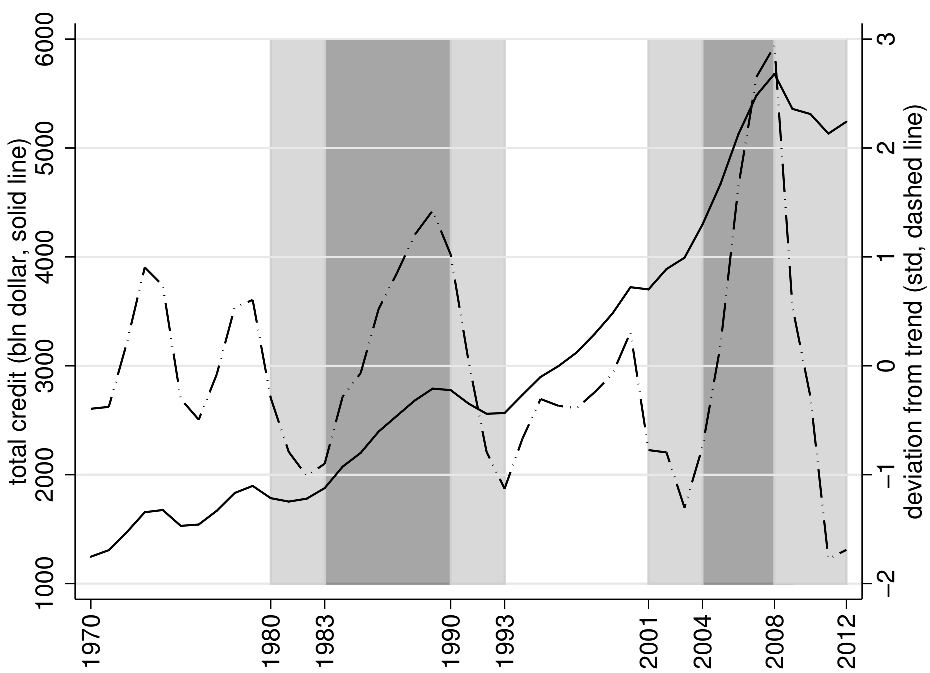
We denote the level of total credit in domestic currency deflated by the consumer price index in economy i and year t by TC_{it}. We compute the trend in TC_{it} using the Hodrick-Prescott filter with a smoothing parameter of 100. We denote the deviation of total credit from its trend (i.e., the cyclical component) $\widetilde{TC}_{it}$. The standard deviation of $\widetilde{TC}_{it}$ is $\sigma(\widetilde{TC}_{it})$. Note that $\sigma(\widetilde{TC}_{it})$ is not computed based on the pooling of all economies but is economy-specific, so that cyclical movements are economy-specific.

We identify credit booms as follows. For each economy, we first identify peaks in which $\widetilde{TC}_{it} > \alpha\sigma(\widetilde{TC}_{it})$ with $\alpha = 1$, as in Braun and Larrain (2005): the cyclical component of total credit is more than one standard deviation above the trend. Then we go back in time until we find a local trough. A local trough is defined as the latest preceding year for which $\widetilde{TC}_{it} < \widetilde{TC}_{it-1}$ and $\widetilde{TC}_{it} < \widetilde{TC}_{it+1}$ both hold: the cyclical component $\widetilde{TC}_{it}$ is lower than in both the previous and posterior years. We then define a binary variable "boom" which takes value one for years between the peak and trough (excluding the trough year), and zero otherwise.

We employ the same procedure to identify credit busts. We first identify troughs, defined as years for which $\widetilde{TC}_{it} < -\alpha\sigma(\widetilde{TC}_{it})$ for $\alpha = 1$ holds: the value of the cyclical component of total credit is more than one standard deviation below trend. Once a local trough is found, we then go back in time until we find a local peak. A local peak is defined as the closest preceding year for which $\widetilde{TC}_{it} > \widetilde{TC}_{it-1}$ and $\widetilde{TC}_{it} > \widetilde{TC}_{it+1}$ both hold: $\widetilde{TC}_{it}$ is higher than in both the previous and posterior years. We then define a binary variable "bust" which takes the value one from the year after the peak (i.e. excluding the peak year) to the trough, and is zero otherwise.

Those economy-year observations which are not identified as either boom or bust are labelled normal years. Thus, this methodology identifies three phases of the credit cycle, each with a duration of one or several years. Figure 1 illustrates the results of this procedure for the U.S., showing credit boom and bust phases (shaded dark and light) and normal periods (non-shaded) from 1970 to 2012.

Figure 1. : Credit Cycle Episodes: The United States, 1970-2012



IV. Credit Booms and Busts: a Descriptive Exploration

By applying this methodology, we come to a total of 187 episodes, of which 63 booms, 63 busts and 60 normal episodes. The data appendix lists all countries, years covered, and the years in which credit cycle episodes fell. In this subsection we explore the distribution, duration and severity of cycle episodes. We also study transitions between episodes.

Temporal distribution

Figure 2 describes the distribution of credit booms and busts over time. Panel (2a) highlights that the panel used is highly unbalanced, as data for most economies is not available before the 1990s. Long time series going back to the 1970s include the U.S., Japan, Germany, the U.K and Switzerland. Due to data availability, the sample covers mostly advanced economies. Some emerging economies such as Brazil, Chile, India, Indonesia, Morocco and the Philippines are included. We refer to Table A1 for a full list.

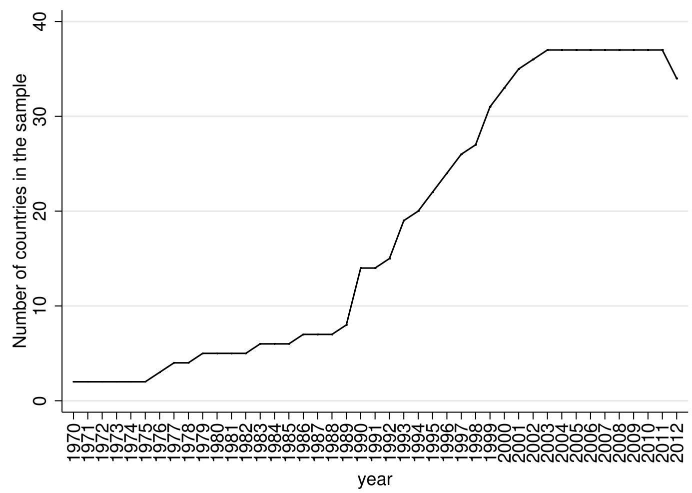
Panels (2b) and (2c) show that credit booms in this sample are concentrated in the mid-1990s and between 2004 and 2007. Credit busts occur mostly in or around that same window, except for another peak in the credit bust distribution post-2008. The graphs also show that in this sample, most credit booms and busts are in advanced economies, simply due to their stronger presence in the sample. But strikingly, in the spate of credit busts in the 2000-2005 years, emerging economies are strongly represented.

Duration and severity

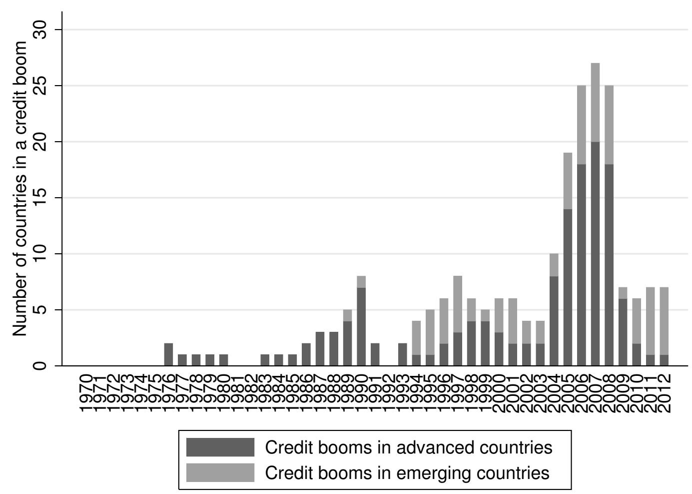
In Table 1 we study frequency, duration, amplitude and slope of credit as a share of GDP, for advanced and emerging economies over the credit cycle. Duration is the number of years covered by each cyclical phase. Amplitude measures the difference between the value at the end and the beginning of a phase. The

Figure 2. : The distribution of credit booms and busts over time

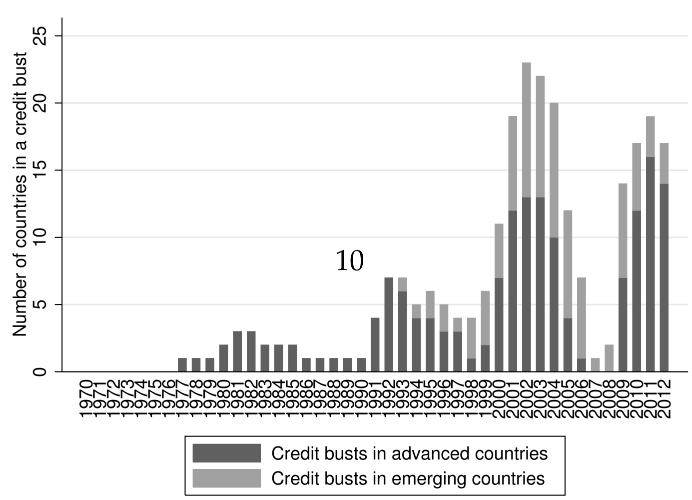
(a) Sample coverage



(b) Credit booms



(c) Credit busts



slope is the ratio of amplitude to duration; it captures the speed of change of the variable measured. We report the median to mitigate the influence of extreme values.

We find that the frequencies of booms and busts are similar. Approximately 30 percent of observations are identified as booms, 30 percent are busts and the rest are normal times. This division holds across the two sub-samples of advanced and emerging economies economies. In advanced economies, a typical boom lasts 5 years, which is slightly longer than a bust, which lasts 4 years. In emerging economies the duration of a credit boom (4 years) is shorter than a bust (5 years). Overall, the normal period has the longest duration. Normal periods are significantly longer in advanced economies (7 years) than in emerging economies (4.5 years).

The median amplitude of credit booms is 10.9 percentage points change in the credit/GDP ratio. This works out at a slope of 3.6 percentage points increase per annum. In a typical bust, the credit-to-GDP ratio drops by 1.4 percentage points, equivalent to a -0.4 percentage points slope. The amplitude and slope of a credit boom are both slightly larger in advanced economies than in emerging economies. However, the amplitude, slope and severity of a typical credit bust in emerging economies is twice larger than in advanced economies. The median credit-to-GDP ratio drops by 1.7 percentage points, compared to 0.2 in advanced economies.

Transitions

Are credit booms typically followed by credit busts? The transition matrices in Table 3 show that this is true for 59% of all booms. For brevity, let us label booms-followed-by-busts as 'bad' booms. We observe that the probability of booms being 'bad' is significantly higher for advanced economies (65%) than for emerging economies (47%).

Over the entire sample and in advanced economies, normal periods are about

Table 1—: Credit cycle phases: descriptives

	Number	Proportion of years	Duration	Amplitude	Slope
Panel A. The Whole Sample (37 countries, 187 episode)					
Boom	63	0.29	4	10.9	3.6
Bust	64	0.32	4	-1.4	-0.4
Normal	60	0.39	6	3.3	0.8
Panel B. Advanced countries (22 countries, 116 episode)					
Boom	38	0.28	5	11.5	3.7
Bust	42	0.32	4	-0.2	-0.03
Normal	36	0.34	7	4.6	1.1
Panel C. Emerging countries (15 countries, 71 episodes)					
Boom	25	0.29	4	9.2	2.6
Bust	22	0.34	5	-1.7	-0.28
Normal	24	0.37	4.5	0.3	0.1

Note: The medians of duration, amplitude and slope are reported.

equally likely to be followed by boom or bust. In emerging economies, the probability of a bust is slightly larger (56%). Credit busts are most often followed by credit booms (64% of all busts) rather than normal periods.[3] This is again somewhat more often the case in advanced economies (69% of all busts, compared to 57% for emerging economies). Taken together, these descriptives suggest that credit cycles appear more volatile in advanced economies than emerging economies.

Credit composition over the credit cycle

Our dataset provides us with a unique opportunity to examine the composition of bank credit over the credit cycle. In Figure (3a) and Figure (3b) we show the median amplitudes of the four different credit categories, for the whole sample and the two subsamples.[4] Figures (3c) and (3d) plot the amplitude of four

[3]Note that this sequence is partly by construction, since busts depress trend growth so that the following phase is more likely to be a boom.

[4]Using slope instead of amplitude, we observe similar patterns. The graphs are available upon request.

Table 2—: Transition Matrices

Panel A. The Whole sample (150 episodes)				
		To		
		Boom	Bust	Normal
	Boom	0.00	33(58.9)	23(41.1)
From	Bust	29(64.4)	0.00	16(35.6)
	Normal	23(46.9)	26(53.1)	0.00
Panel B. Advanced countries (94 Episodes)				
		To		
		Boom	Bust	Normal
	Boom	0.00	24(64.9)	13(35.1)
From	Bust	18(69.2)	0.00	8(30.8)
	Normal	15(48.4)	16(51.6)	0.00
Panel C. Emerging countries (56 episodes)				
		To		
		Boom	Bust	Normal
	Boom	0.00	9(47.4)	10(52.6)
From	Bust	11(57.9)	0.00	8(42.1)
	Normal	8(44.4)	10(55.6)	0.00

Note: The last 37 episodes from each country are excluded. Number denotes the episode counts. Transition probabilities are in parentheses.

different types of credit in good and bad booms, for the whole sample and two subsamples.

We find that a credit boom is on average characterized by a simultaneous increase in both non-financial business credit and mortgage credit and, to a lesser extent, consumer loans and financial business credit. The increase in mortgage credit is much more pronounced in advanced economies.

During credit busts, non-financial business credit experiences the most significant decline of all credit categories. The magnitude is similar across country groups. Since credit to non-financial business is most directly related to output, this finding fits in with the disruptive impact of a credit bust on the economy. Normal periods are associated with considerable increases in mortgage credit, particularly in advanced economies.

During credit busts, household mortgage credit continues to increase as a share of GDP. This stands in contrast to business credit, which falls faster than GDP. A number of recent papers (IMF, 2012; Mian and Sufi, 2014) have discussed how this household debt problem is another part of the explanation for the recession that typically accompanies a credit bust. Again, the increase in mortgage debt as a share of GDP is significantly larger in advanced economies.

How do good booms (which are not followed by busts) differ from bad booms, which are followed by busts? On average the magnitude of bad booms (the increase in all four types of credit) is larger than good booms. This supports the general caution towards overly rapid credit growth. But the most striking difference is in panel (c). The share of mortgage credit in bad booms increases almost three times faster than is the case in good booms. The increase of mortgage credit in a bad boom is also much larger (again, by about a factor three) than is the increase in credit to nonfinancial business. This dramatic change in credit composition is the one striking difference between good and bad booms. In addition, in a bad boom also the other types of credit other than to nonfinancial business (that is, credit to nonbank financial firms and consumer credit) rise faster than in a good boom.

If we break this result down to the two groups of economies, it turns out to be an advanced-economy phenomenon. In emerging economies, even in a bad boom the increase in credit to nonfinancial business is larger than the increase in household mortgage credit. However, in emerging economies consumer credit increases much more than in advanced economies during a bad boom. Overall, this underlines the contribution of household credit to financial fragility noted in other papers. The trends discussed here suggest that credit busts are essentially *mortgage* credit booms gone wrong, to paraphrase Schularick and Taylor (2012). This poses the question: does credit composition not only describe, but also help predict credit boom/bust dynamics, jointly with other variables? We address this in the analysis in the next sections.

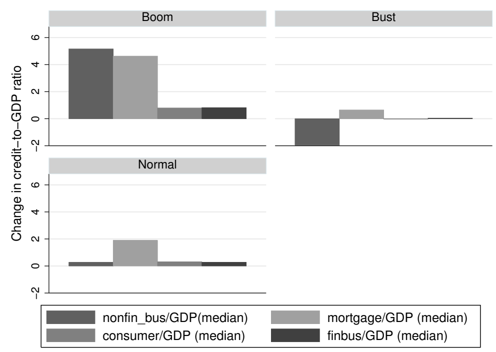
V. Event Analysis

In this section we compare the behavior of mortgage credit in credit booms and busts to that of variables identified in the literature as driving credit cycle dynamics. We characterize credit composition by the share of mortgages in total credit ($MSHARE$) and the change in the share of mortgages in total credit ($MSHARECHANGE$). IMF (2011) document three other factors strongly associated with credit booms: surges in capital inflows($CAPFLOW$), a financial sector reforms index (CRQ)and productivity gains (TFP growth, ($GRTFP$)). In view of the significance of both house prices and credit growth in the credit cycle, we also study the behaviour of the change in real house prices ($HPCHANGE$). [5]

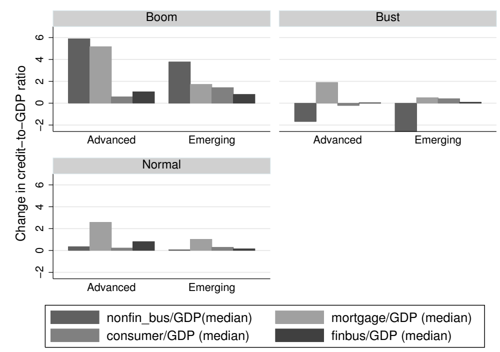
[5]Net capital inflows as a percentage of GDP ($CAPFLOW$) were taken from the IMF Balance of Payment Statistics (BOPS) databank. Financial sector reform is proxied by a credit regulation quality index (CRQ) drawn from the Fraser Institute Index of Economic Freedom. This index is composed of the percentage of deposits held in privately owned banks, the extent to which banks face competition from foreign banks, the percentage of credit extended to the private sector and the presence of interest-rate controls. Thus, higher values of this index indicate more financial freedom; it is a financial de-regulation index. TFP growth ($GRTFP$), taken from from the Penn World Table, version 8.0. Both CRQ and GRTFP measures are available until 2011. For 2012, we use the value of 2011. Data on real house prices ($HPCHANGE$) were etrieved data from the Bank for International Settlements (BIS) Residential Property Price Statistics. This variable is available for only 30 economies, and a somewhat shorter time span. See also Table 3.

Figure 3. : Changing credit composition over the credit cycle

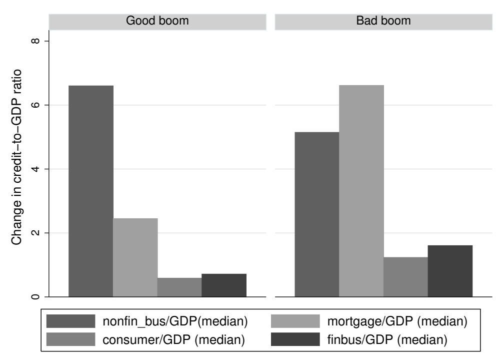
(a) Credit composition



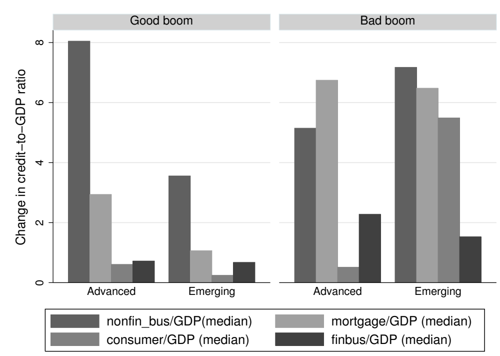
(b) Credit composition per country group



(c) Different credit booms



(d) Different credit booms per country group



Note: The median is used.

Table 3 panel B summarizes the definitions, sources and descriptive statistics of all these variables.

Following Gourinchas and Obstfeld (2012), we explore the behaviour of these variables through credit booms and busts, controlling for country-specific fixed effects. This yields stylized facts which motive the multinomial logit analysis in the next section. We estimate the conditional expectation of a variable y_{it} (where i denotes country and t denotes year) as a function of the distance in time from credit booms and busts, relative to the normal period reference. The fixed-effect panel specification is:

$$y_{it} = \alpha_i + \beta_{bs}\delta_{bs} + \beta_{cs}\delta_{cs} + \varepsilon_{it} \tag{1}$$

where δ_{js} denotes a dummy variable equal to 1 when country i is s periods away from an event j in period t. The index j denotes the event type, i.e. a credit boom (b) and a credit bust (c), respectively. The event window around credit boom and bust episodes is set to 7 years: 3 years before and 3 years after. α_i is a country-specific fixed effects; ε_{it} is an error term. The coefficients β_{js} are of primary interest. They measure to what extent variable y_{it} behaves differently over the event window $-3 \leq s \leq 3$ relative to the normal period reference level.[6]

Figure 4 reports estimation results of equation (1). This shows the behavior of the five variables around credit booms and busts, relative to normal periods. The beginning of each is indexed by T. Panels (4a) and (4b) in the top row show that the share of mortgage credit in total credit increase in the run-up to a boom. It then falls in the first three years of a boom and stabilizes in $T + 3$. A credit bust, in contrast, is preceded by a decline in the share of mortgage credit in total

[6] Alternatively, we could estimate two separate equations for credit boom and bust episodes. In this set-up, the effect of credit booms (busts) are estimated relative to both bust (boom) and normal episodes, rather than only the normal period. Although the reference periods are different, we find that the results are quantitatively similar.

Table 3—: Descriptive statistics

Name	Definition	Source	count	mean	sd	min	max
Panel A. Dependent Variable							
BOOM	takes value 1 in the first year of a credit boom,	own calculation based on Bezemer et al. (2014)	773	0.524	0.832	0	2
	value 2 in other boom years, and 0 for all other years						
BUST	takes value 1 in the first year of a credit bust,	own calculation based on Bezemer et al. (2014)	773	0.541	0.841	0	2
	value 2 in other bust years, and 0 for all other years	own calculation based on Bezemer et al. (2014)	215	0.637	0.482	0	1
BADBOOM	A dummy variable which takes on the value of 1						
	if a credit boom is followed by a bust, i.e. a bad boom						
	and 0 for other booms.						
Panel B. Independent Variable							
MSHARECHANGE	Annual change in the share of mortgage credit	Bezemer et al. (2014)	727	0.721	1.963	-12.514	12.616
GRTFP	Total factor productivity growth	Penn World Table 8.0	773	0.307	2.481	-15.130	8.749
CAPFLOW	Net capital flow as a percentage of GDP	IMF BOPS	773	-0.264	5.909	-25.900	14.600
	(+ net capital inflow; - net capital outflow)						
CRQ	Credit regulation quality	Frazer Institute	773	8.505	1.380	2.640	10.000
HPCHANGE	Annual real house price change, in percentage	BIS	570	4.965	10.636	-34.633	78.012

credit during each of the three preceding years. The growth in capital flows (panel (4c)) is positive in the years preceding a boom and rising throughout the boom. A bust is characterized by a capital flows reversal in the preceding year and steeply rising capital outflows in the years T, $T+1$ and $T+2$.

The credit de-regulation (financial reform) measure in panel (4d)) takes clearly higher values in booms than in busts. Its value increases in the years before, during and after the start of a boom and then falls back to the pre-boom level. In the two years before a bust, the regulation index value falls; it remains stable during a bust.

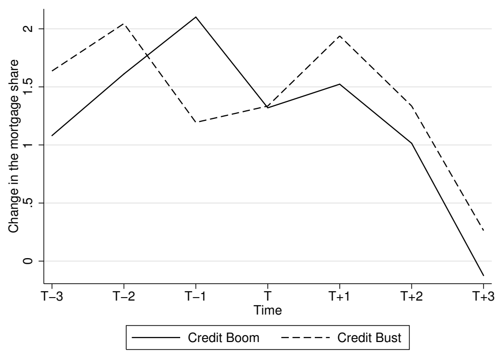
Panel (4e) shows that the start of a credit boom coincides with a sharp upturn in productivity growth, which turns out to be a spike rather than a trend. The boom is preceded by two years of decreasing TFP growth, and this trend continues after the spike in T and $T+1$. In a credit bust, a mirror image pattern obtains: a sharp fall in productivity during the start of the bust, with TFP growth bouncing back to previous levels from $T+1$. TFP growth is higher three years after the start of a bust than it is three years after the start of a boom.

Panel (4f) shows two simple patterns, one hump-shaped and one U-shaped. The change in house prices is positive and rising in the run-up to a boom and negative and falling in the run-up to a bust. Both these trends reverse upon the start of the boom or bust; in a boom, that reversal occurs only after the first year.

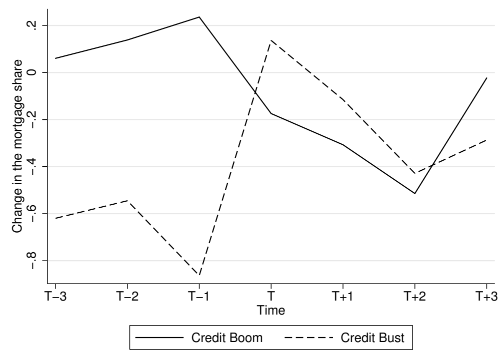
These outcomes are broadly consistent with the literature (IMF, 2011; Mendoza and Terrones, 2012; Gourinchas and Obstfeld, 2012). Amoing other things, they suggest a role for mortgage credit somewhat similar to capital flows. A rise prompts a boom, a fall sets the scene for the bust. Going beyond this one-phase event analysis, we now turn to analysis of a boom-bust sequence. How do these variables, and especially the share of mortgage credit in total credit, behave before a bad boom occurs?

Figure 4. : Event Analysis Results

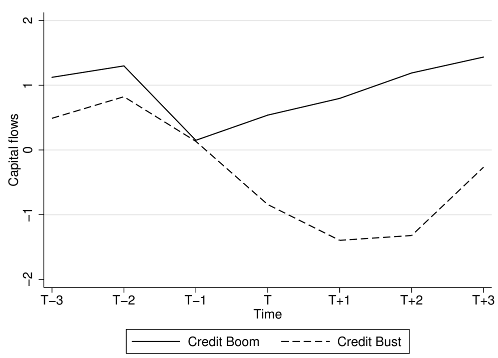
(a) Mortgage share



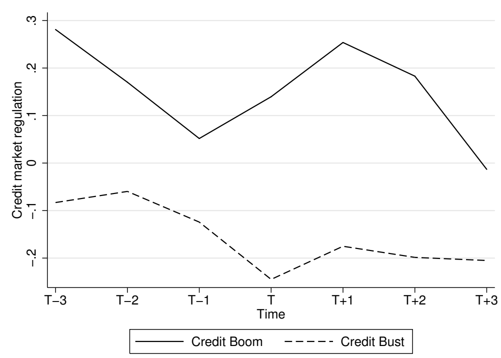
(b) Change in the mortgage share



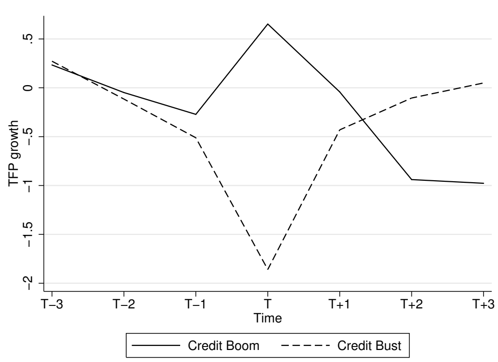
(c) Capital flows



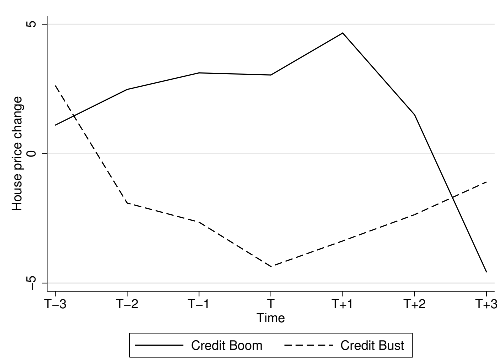
(d) Credit regulation quality



(e) TFP growth



(f) Change in house price



VI. Does Credit Composition Predict Boom-Bust?

In this section we analyze the role of mortgage credit growth as an early predictor of credit booms, credit busts and of credit booms followed by busts (i.e., 'bad' booms). We follow other early warning systems methodologies (e.g. Caggiano and Leonida (2013) on banking crises and Bussiere and Fratzscher (2006) on currency crises) and estimate a multinomial logit model. [7] For for each country i at year t, the dependent variable $Y_{i,t}$ in the multinomial logit model takes one of three values: $Y_{i,t} = 1$ in the first year of a credit boom (or bust), i.e., $Y_{i,t} = 2$ in other years following the first year of a credit boom (or bust) and $Y_{i,t} = 0$ in 'tranquil' (neither boom nor bust) years. The tranquil regime $Y_{i,t} = 0$ is the baseline to provide identification for the following model:

$$\begin{aligned} Pr(Y_{i,t} = 0) &= \frac{1}{1 + exp(X_{i,t-1}\beta^1) + exp(X_{i,t-1}\beta^2)} \\ Pr(Y_{i,t} = 1) &= \frac{exp(X_{i,t-1}\beta^1)}{1 + exp(X_{i,t-1}\beta^1) + exp(X_{i,t-1}\beta^2)} \\ Pr(Y_{i,t} = 2) &= \frac{exp(X_{i,t-1}\beta^2)}{1 + exp(X_{i,t-1}\beta^1) + exp(X_{i,t-1}\beta^2)} \end{aligned} \tag{2}$$

This implies that β^1 measures the effect of a change in the independent variables $X_{i,t-1}$ on the probability of the start of a credit boom (or bust) relative to the probability of being in the tranquil regime. Coefficient β^2 measures the same effect for the continuation of a credit boom (or a bust) relative to the probability of being in a tranquil regime:

[7] We prefer the multinomial over the binomial logit model so as to avoid so-called *crisis duration bias* (Caggiano and Leonida, 2013). This effect arises because in the years after the onset of an event, variables correlated to this event are likely to be affected by the event itself. For instance, in our setting, the share of mortgage credit in total credit tends to decline as a result of the start of a credit boom, as we saw in Figure 4. By treating crisis years other than the first as non-crisis observations, or omitting them altogether from the sample, we would ignore potentially valuable information about which variables are associated with the continuation of an event rather than the start. In the Appendix we explore whether including this information makes a difference to the results.

$$
\begin{aligned}
\frac{Pr(Y_{i,t}=1)}{Pr(Y_{i,t}=0)} &= exp(X_{i,t-1}\beta^1) \\
\frac{Pr(Y_{i,t}=2)}{Pr(Y_{i,t}=0)} &= exp(X_{i,t-1}\beta^2)
\end{aligned} \tag{3}
$$

The key advantage of a multinomial logit model is that it permits an explicit modeling of three different regimes and the distinction between two parameter vectors β^1 and β^2. Estimating this model allows us to address the questions: which factors cause the start and continuation of a credit boom or bust? In a second set of estimations, we also address the question "what triggers a bad boom – that is, what triggers a credit boom which is followed by a credit bust?". Here we adopt a binomial logit model. We only use the sample of credit boom years. For each country *i* at year *t*, the dependent variable $Y_{i,t}$ has two outcomes: a bad credit boom, i.e., $Y_{i,t}$=1 and a good credit boom $Y_{i,t} = 0$. We choose the probability of being in a good credit boom $Y_{i,t} = 0$ as the baseline regime. The probability of being in a 'bad' credit boom is defined as:

$$
Pr(Y_{i,t}=1) = \frac{exp(X_{i,t}\beta^3)}{1+exp(X_{i,t}\beta^3)} \tag{4}
$$

Where β^3 measures the effect of a change in the independent variable $X_{i,t}$ on the probability of being in a bad boom relative to a good one. Note that all independent variables are expressed at year *t*.

A. Credit Boom Determinants

Panel A in Table 4 shows the estimated probability of entering a credit boom, with a non-boom (i.e. normal or bust) period as the baseline. Panel B addresses the possibility of crisis duration bias. It reports the probability of *remaining* in a credit boom. In both panels A and B , we add control variables common in the literature. We are especially interested in the role of house prices and its interaction with mortgage credit growth as harbingers of financial fragility, emphasized by Borio and Lowe (2004); Mendoza and Terrones (2012); Davis and Zhu (2009).

We find that crisis duration bias appears relevant in this sample: the coefficients for the independent variables are very different in Panel A and B. We concentrate on Panel B results.

The results in panel B appear to confirm that house prices matter in conjunction with credit composition. Change in the lagged share of mortgage credit in total credit in and of itself is not a good predictor of either starting a credit boom, or remaining in a credit boom once it started. But the lagged interaction of house price change with the change in the mortgage credit share is a significant predictor for credit boom continuation. Once this is accounted for, the effect of change in the lagged share of mortgage credit itself is robustly negative. These results suggest that credit composition matters, but only in conjunction with asset price changes. In addition, the lagged change in house prices also carries a highly significant coefficient in Panel B. Control variables have the expected signs.

In Table 5 we run a number of robustness checks for this credit boom model (Panel A) as well as for the credit bust model reported below (Panel B). Following Caggiano and Leonida (2013), we compare the Table 4 model with three binomial logit model. In this way we to check how taking into account duration bias matters to the outcomes. The first specification is a binomial logit model where we assume that credit booms last only one year. The dependent variable is a dummy which takes value one when the economy enters a credit boom and zero otherwise, excluding other credit boom years. Columns (1a)-(4a) in Table 5 show the results. The second specification is a binomial logit model where we drop all observations after the initial year of a credit boom. The dependent variable is a dummy which takes value one for the initial year of a credit boom and zero otherwise (columns (5a)-(8a)). The third specification is a logit model where the

Table 4—: What triggers a credit boom?

	(1)	(2)	(3)	(4)
Panel A. Initital year of a credit boom				
L.MSHARE	0.077	0.076	0.086	0.022
	(0.058)	(0.057)	(0.069)	(0.092)
L.GRTFP		0.051	0.043	0.035
		(0.075)	(0.078)	(0.081)
L.CAPFLOW		-0.023	-0.020	-0.023
		(0.025)	(0.027)	(0.029)
L.CRQ		0.020	-0.052	-0.056
		(0.107)	(0.132)	(0.133)
L.HPCHANGE			0.049***	0.041**
			(0.016)	(0.017)
L.MSHARE*L.HPCHANGE				0.010
				(0.007)
Constant	-2.197***	-2.408***	-2.111*	-2.058*
	(0.164)	(0.929)	(1.164)	(1.174)
Panel B. Boom years following the initial year				
L.MSHARE	-0.028	-0.105*	-0.169**	-0.229***
	(0.053)	(0.056)	(0.072)	(0.074)
L.GRTFP		0.196***	0.108*	0.103*
		(0.048)	(0.057)	(0.057)
L.CAPFLOW		0.101***	0.130***	0.125***
		(0.022)	(0.027)	(0.026)
L.CRQ		0.447***	0.355***	0.356***
		(0.086)	(0.102)	(0.103)
L.HPCHANGE			0.052***	0.044***
			(0.011)	(0.012)
L.MSHARE*L.HPCHANGE				0.012**
				(0.005)
Constant	-0.926***	-4.857***	-4.260***	-4.268***
	(0.101)	(0.769)	(0.929)	(0.943)
Observation	597	597	466	466

dependent variable takes value one for all boom years and zero otherwise. This specification makes use of the full sample (columns (9a)-(12a)).

The results in Panel A on the credit boom models show that alternative specifications matter. In particular, the multinomial logit findings are robust to a binomial specification where the dependent variable takes value one for all boom years and zero otherwise (columns (9a)-(12a)), but not to specifications which do not take account for boom years beyond the start year. In columns (1a)-(4a) and (5a)-(8a), results for the lagged change in the mortgage credit share, with or without lagged house price interaction, are all insignificant.

B. Credit Bust Determinants

In analogy to Table 4, Table 6 shows the multinomial logit results for the start (Panel A) and continuation (Panel B) of a credit bust. Probabilities are estimated relative to normal or boom periods. Again, we find that accounting for duration bias is important; we concentrate on the Panel B results. These show that an increase in the lagged change of the mortgage credit share is positively associated with the probability that a credit bust continues. House price declines have the same effect. The lagged interaction of credit composition and house price declines is not a significant predictor of credit bust continuation. Of the control variables, capital flow reversals are a robust predictor.

Panel B in Table 5 shows alternative binomial logit specifications. Similar to Panel A in Table 5, this demonstrates again that the multinomial logit findings are robust only to a binomial logit specification where the dependent variable takes value one for all bust years and zero otherwise. We even observe an opposite and significant effect in the specification where the dependent variable takes value one when the economy enters a credit bust and zero otherwise, excluding other credit boom years. The reason, as noted, is that this approach assumes (erroneously) that credit busts last only one year. The explorations in Table 5 show that this assumption could lead to misleading inferences on the determinants of

Table 5—: Alternative Specifications: Binomial Models

	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)	(7a)	(8a)	(9a)	(10a)	(11a)	(12a)
Panel A. Credit Booms												
L.MSHARECHANGE	0.084	0.099*	0.120*	0.101	0.086	0.080	0.111	0.056	-0.002	-0.056	-0.105*	-0.170***
	(0.058)	(0.056)	(0.067)	(0.085)	(0.068)	(0.067)	(0.083)	(0.098)	(0.044)	(0.045)	(0.058)	(0.064)
L.GRTFP		0.014	0.024	0.021		0.051	0.052	0.046		0.152***	0.092*	0.087*
		(0.070)	(0.073)	(0.075)		(0.075)	(0.081)	(0.082)		(0.047)	(0.051)	(0.051)
L.CAPFLOW		-0.046*	-0.051**	-0.053**		-0.023	-0.014	-0.018		0.065***	0.084***	0.080***
		(0.024)	(0.024)	(0.026)		(0.028)	(0.031)	(0.032)		(0.017)	(0.021)	(0.021)
L.CRQ		-0.088	-0.158	-0.162		0.020	-0.032	-0.037		0.336***	0.256***	0.255***
		(0.101)	(0.128)	(0.129)		(0.106)	(0.129)	(0.129)		(0.073)	(0.089)	(0.090)
L.HPCHANGE			0.026**	0.023			0.048***	0.038**			0.051***	0.043***
			(0.013)	(0.015)			(0.016)	(0.019)			(0.011)	(0.012)
L.MSHARECHANGE*L.HPCHANGE				0.002				0.007				0.012***
				(0.006)				(0.008)				(0.004)
Constant	-2.531***	-1.846**	-1.496	-1.447	-2.206***	-2.416***	-2.296**	-2.201*	-0.677***	-3.578***	-3.107***	-3.093***
	(0.161)	(0.880)	(1.132)	(1.142)	(0.167)	(0.925)	(1.150)	(1.151)	(0.092)	(0.649)	(0.801)	(0.811)
ROC	0.581	0.587	0.63	0.63	0.571	0.564	0.631	0.628	0.515	0.654	0.693	0.696
Obs	597	597	466	466	430	430	330	330	597	597	466	466

	(1b)	(2b)	(3b)	(4b)	(5b)	(6b)	(7b)	(8b)	(9b)	(10b)	(11b)	(12b)
Panel A. Credit Busts												
L.MSHARECHANGE	-0.192**	-0.188**	-0.244**	-0.244**	-0.137*	-0.122	-0.157	-0.158	0.080*	0.106**	0.111*	0.131*
	(0.082)	(0.085)	(0.100)	(0.101)	(0.079)	(0.084)	(0.100)	(0.101)	(0.045)	(0.046)	(0.060)	(0.070)
L.GRTFP		-0.046	-0.109	-0.109		-0.074	-0.129*	-0.128		-0.090**	-0.048	-0.045
		(0.062)	(0.072)	(0.073)		(0.063)	(0.078)	(0.078)		(0.037)	(0.048)	(0.048)
L.CAPFLOW		0.020	-0.001	-0.001		0.010	-0.007	-0.007		-0.026*	-0.032**	-0.030*
		(0.029)	(0.029)	(0.029)		(0.026)	(0.028)	(0.028)		(0.014)	(0.016)	(0.016)
L.CRQ		0.072	0.054	0.054		0.047	0.042	0.042		-0.053	-0.032	-0.029
		(0.131)	(0.166)	(0.166)		(0.135)	(0.188)	(0.188)		(0.071)	(0.098)	(0.098)
L.HPCHANGE			-0.020	-0.020			-0.028	-0.028			-0.041***	-0.037***
			(0.021)	(0.021)			(0.020)	(0.021)			(0.012)	(0.012)
L.MSHARECHANGE*L.HPCHANGE				0.000				-0.001				-0.005
				(0.007)				(0.007)				(0.005)
Constant	-2.251***	-2.869**	-2.623*	-2.623*	-1.908***	-2.312**	-2.180	-2.174	-0.562***	-0.130	-0.238	-0.265
	(0.146)	(1.142)	(1.458)	(1.459)	(0.148)	(1.175)	(1.649)	(1.655)	(0.091)	(0.611)	(0.862)	(0.861)
AUC	0.641	0.635	0.638	0.639	0.607	0.6	0.626	0.627	0.563	0.599	0.64	0.643
Obs	597	597	466	466	425	425	342	342	597	597	466	466

credit busts.

C. *When Do Credit Booms Go Bust?*

This takes us to addressing the question when a credit boom turn into a bust. Conditional on the occurrence of a credit boom, which factors increase the probability of a credit bust? In other words, which features allow us to infer an increased probability of a bad boom?

Table 7 shows estimation results. We now estimate a binomial logit model, appropriate to the issue we address. The dependent variable is a dummy which takes the value one when a boom is bad, (i.e. is followed by a bust) and zero otherwise. We utilize the same control variables as above and find that the lagged change in the level of the share of mortgage credit in total credit increases the probability of a bad boom, strongly and very significantly. This is robust to adding the control variables, which increases the size of the coefficient. The other robustly significant variable is lagged capital inflows. Lagged house price changes are positively, but not robustly associated with larger probability of bad booms. The interaction of lagged credit composition change and lagged house prices carries a negative, weakly significant coefficient. Since credit composition (rather than house prices) is perhaps more amenable to being a policy variable, a useful alternative interpretation of the interaction terms is that for a given level of house price increase, less mortgage expansion tempers the risk of a bad boom.

To assess the predictive power of the logit specifications in Table 7, we use the receiver operating characteristic (ROC) curve method. The ROC curve is a plot of the true positive rate versus the false positive rate. The predictive power of each specification can be mesaured by the area under the curve (AUC) measure. If the AUC is larger than 0.5 (which is the probability of a coin toss), the independent variables have predictive power. As shown in Table 7, the model with the share of mortgages in total credit as the only independent variable (column

Table 6—: What triggers a credit bust?

	(1)	(2)	(3)	(4)
Panel A. Initital year of a credit bust				
L.MSHARECHANGE	-0.152*	-0.135	-0.179*	-0.167
	(0.084)	(0.089)	(0.106)	(0.109)
L.GRTFP		-0.077	-0.129*	-0.126
		(0.065)	(0.076)	(0.077)
L.CAPFLOW		0.008	-0.014	-0.014
		(0.030)	(0.030)	(0.030)
L.CRQ		0.050	0.036	0.037
		(0.133)	(0.167)	(0.167)
L.HPCHANGE			-0.034	-0.033
			(0.023)	(0.023)
L.MSHARECHANGE*L.HPCHANGE				-0.004
				(0.008)
Constant	-1.902***	-2.327**	-2.099	-2.101
	(0.148)	(1.158)	(1.471)	(1.470)
Panel B. Bust years following the initial year				
L.MSHARECHANGE	0.158***	0.189***	0.212***	0.273***
	(0.053)	(0.055)	(0.072)	(0.092)
L.GRTFP		-0.091**	-0.024	-0.017
		(0.039)	(0.052)	(0.053)
L.CAPFLOW		-0.037**	-0.040**	-0.035**
		(0.015)	(0.017)	(0.017)
L.CRQ		-0.081	-0.064	-0.057
		(0.078)	(0.111)	(0.111)
L.HPCHANGE			-0.042***	-0.030**
			(0.012)	(0.012)
L.MSHARECHANGE*L.HPCHANGE				-0.011
				(0.007)
Constant	-0.908***	-0.259	-0.361	-0.460
	(0.102)	(0.675)	(0.979)	(0.983)
Panel C. Statistics				
Observation	597	597	466	466

Table 7—: When do credit booms go bust?

	(1)	(2)	(3)	(4)
L.MSHARE	0.04***	0.038***	0.058***	0.070***
	(0.011)	(0.011)	(0.017)	(0.021)
L.GRTFP		0.144*	0.203*	0.218*
		(0.075)	(0.109)	(0.114)
L.CAPFLOW		0.119***	0.103***	0.102***
		(0.028)	(0.037)	(0.038)
L.CRQ		0.351***	0.021	0.039
		(0.134)	(0.193)	(0.201)
L.HPCHANGE			0.018	0.077**
			(0.013)	(0.036)
L.MSHARE*L.HPCHANGE				-0.002*
				(0.001)
Constant	-0.643	-3.767***	-1.718	-2.264
	(0.391)	(1.095)	(1.571)	(1.615)
AUC	0.673	0.746	0.735	0.746
Obs	200	200	157	157

1) has an AUC of 0.673. Adding three additional independent variables, namely productivity growth, net capital inflows and financial regulation in column (2) considerably improves the AUC value to 0.746. However, adding changes in house prices and its interaction with the mortgage share in columns (3) and (4) does not increase the AUC value. These two variables do not add predictive power.

VII. Summary and Conclusion

Some credit booms collapse into a hard landing with costs to the real economy, while other credit booms benefit output growth and productivity and unwind gradually. In this paper we asked which credit boom features may help us observe whether a credit boom will be followed by a credit bust. We collected data on 37 economies over 1970-2012 where we distinguish bank loans to nonfinancial business from unsecured consumer credit to households, household mortgage credit and bank credit to nonbank financial firms. We identified 187 credit booms, busts and normal periods and chart the change in the composition of credit over the credit cycle. In multinomial and binominal analyses, we found that the interaction of mortgage credit growth and increasing house prices is a good predictor of a credit boom. We also found that credit booms in which the share of mortgage credit in total bank credit increases more, are credit booms which are more likely to 'go bad', leading to subsequent credit growth contractions. We hope to have opened a fruitful research avenue for future research into credit cycles.

Understanding the difference between 'good booms' of accelerated investment and growth and 'bad booms' ending in credit growth contractions already during the boom would seem to be of great practical value. Adequate policy requires an assessment of the build-up of financial fragility anda reliable warning signal. Rapid credit growth itself may be part of this red flag, but not all fast credit growth is bad. The risk would be to kill good and bad booms alike. The need to differentiate general credit booms from housing booms was recently emphasized by Deputy Managing Director Min Zhu of the IMF in a June 5, 2014 speech. Among other things, he noted that "monetary policy will have to be more concerned than it was before with financial stability and hence with housing markets. The era of 'benign neglect' of house price booms is over" (Zhu, 2014). The present findings may help policy makers to turn from benign neglect to active monitoring of the credit cycle, in support of macroprudential policy over the credit cycle.

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Data Appendix

Country	Code	Time Span	Episode	Boom	Bust	Normal
Australia	AUS	1990-2012	4	2003-2009	2000-2002	1990-1999
					2010-2012	
Austria	AUT	1995-2012	5	1997-2000	2001-2004	1995-1996
				2005-2008	2009-2012	
Belgium	BEL	1999-2012	3	2005-2008	2009-2012	1999-2004
Brazil	BRA	1994-2012	5	1994	2001-2006	1995-2000
				2010-2012		2007-2009
Canada	CAN	1990-2012	5	1990	2000-2004	1991-1999
				2005-2008		2009-2012
Switzerland	CHE	1977-2012	11	1989-1991	1981-1985	1977-1980
				1997-1999	1992-1993	1986-1988
				2006-2007	2000-2005	1994-1996
				2011-2012		2008-2010
Chile	CHL	1983-2012	6	1995-1997	1998-2004	1983-1994
				2005-2008	2009-2010	2011-2012
Czech Republic	CZE	1993-2012	5	1994-1997	1998-2002	1993
				2003-2008		2009-2012
Germany	DEU	1970-2012	9	1976-1980	1986-1989	1970-1975
				1990-1991	1992-1995	1981-1985
				1996-2002	2003-2006	2007-2012
Denmark	DNK	2000-2012	3	2004-2008	2009-2012	2000-2003
Spain	ESP	1992-2012	3	2004-2009	2010-2012	1992-2003
Estonia	EST	1999-2012	3	2005-2008	2009-2012	1999-2004
Finland	FIN	1997-2012	3	2003-2008	1997-2002	
					2009-2012	
France	FRA	1993-2012	6	1993	2001-2004	1994-2000

Continued...

Country	Code	Time Span	Episode	Boom	Bust	Normal
				2005-2008	2011-2012	2009-2010
UK	GBR	1986-2012	6	1987-1990	1991-1996	1986
				2006-2009	2010-2012	1997-2005
Greece	GRC	1990-2012	4	1990		1991-2003
				2004-2010	2011-2012	
Hungary	HUN	1989-2012	6	1989-1990	1995-1996	1991-1994
				1999-2006	2007-2012	1997-1998
Indonesia	IDN	2002-2012	4	2010-2012	2002-2006	2007-2008
					2009	
India	IND	2001-2011	4	2001	2002-2005	2009-2011
				2006-2008		
Ireland	IRL	2003-2012	3	2004-2008	2003	2009-2012
Israel	ISR	1999-2012	5	2000-2002	1999	2003-2005
					2006	2007-2012
Italy	ITA	1998-2012	6	2005-2007	2001-2004	1998-2000
				2010	2011-2012	2008-2009
Japan	JPN	1976-2012	8	1996	1997-1985	1997-1999
				1986-1989	1990-1992	2006-2012
				1993-1996	2000-2005	
Lithuania	LTU	1993-2012	3	2003-2008	1993-2002	
					2009-2012	
Luxembourg	LUX	1999-2012	6	2007-2008	2002-2004	1999-2001
					2011-2012	2005-2006
						2009-2010
Morocco	MAR	2001-2012	3	2001	2002-2005	2006-2012
Mexico	MEX	2000-2012	4	2000	2001-2005	2009-2012
				2006-2008		

Continued…

Country	Code	Time Span	Episode	Boom	Bust	Normal
Netherlands	NLD	1990-2011	5	1990	1991-1997	1998-2006
				2007-2008	2009-2011	
Norway	NOR	1995-2012	4	2006-2008	2001-2005	1995-2000
						2009-2012
New Zealand	NZL	1990-2012	4	2004-2008	2000-2003	1990-1999
					2009-2012	
Philippine	PHL	1997-2012	5	1997	2005-2006	1998-2004
				2010-2012		2007-2009
Poland	POL	1996-2012	4	2007-2009	2000-2006	1996-1999
						2010-2012
Portugal	PRT	1979-2012	6	1997-2002	1992-1996	1979-1991
				2006-2009	2010-2012	2003-2005
Singapore	SGP	1990-2012	7	1994-1998	2004-2006	1990-1993
				2011-2012	2009-2010	1999-2003
						2007-2008
Sweden	SWE	1996-2011	4	2005-2009	1999-2004	1996-1998
					2010-2011	
Turkey	TUR	1993-2012	7	1995-1998	2001-2004	1993-1994
				2010-2012	2008-2009	1999-2000
						2005-2007
United States	USA	1970-2012	8	1983-1990	1980-1982	1970-1979
				2004-2008	1991-1993	1994-2000
					2001-2003	
					2009-2012	

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